ECG Signal Analysis for Myocardial Infarction Detection

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C O N N E X I O N S

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Chapter 1

Introduction[1]

1.1 Introduction

This project undertakes the challenge of extracting features from an EKG signal. The extracted features can later be used for diagnosing heart diseases like Myocardial Infarction (MI), also known as a heart attack. MI will be the context in which we ground our project. An EKG (electrocardiogram) measures the electrical activity of the human heart over a period of time. By taking in an EKG and performing digital signal processing, we can extract the key features of the signal that can help determine a heart condition like MI.

The motivation for this project is the usefulness of its application. According to the American Heart Association's, heart attacks are still the leading cause of death in the U.S. They estimate that around 8 million people suffer from MI in the U.S. The onset of MI can result in discomfort in the chest, severe chest pain, or sudden death.

MI can be properly treated if detected early. Patients consult Cardiologists for diagnoses. However, human expertise not always available. By developing a DSP solution to diagnosing MI, early detection can be made available to more people.

1.2 The problem

When a raw EKG signal is collected, the raw signal is not in a good form for analysis. Features cannot be extracted from this form accurately, and hence MI cannot be diagnosed accurately. This is what a raw EKG signal looks like:

[1] This content is available online at <http://cnx.org/content/m48317/1.1/>.

1.2.1

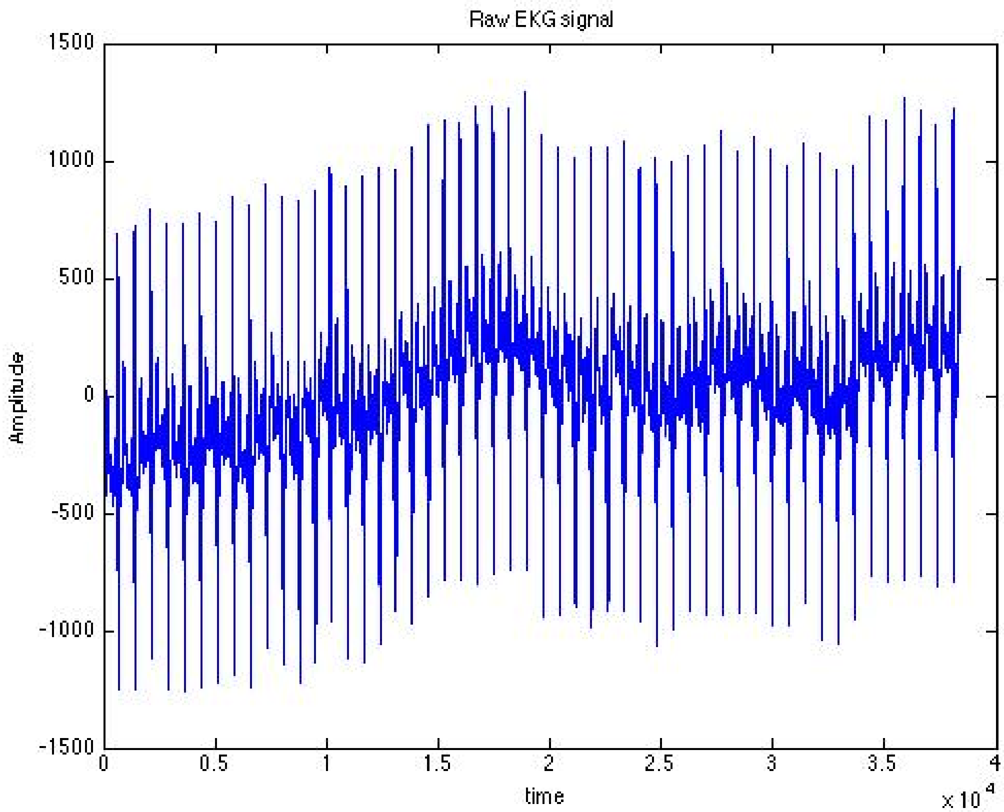


Figure 1.1

You can see that there is noise and the baseline wanders from the horizontal axis. The noise could have came from body movements, nearby electrical devices, and many other sources. Whatever the case, it is important to remove it. Also, it is important to correct the baseline wander, and see the frequency content of the signal, which can contain useful information.

Objective

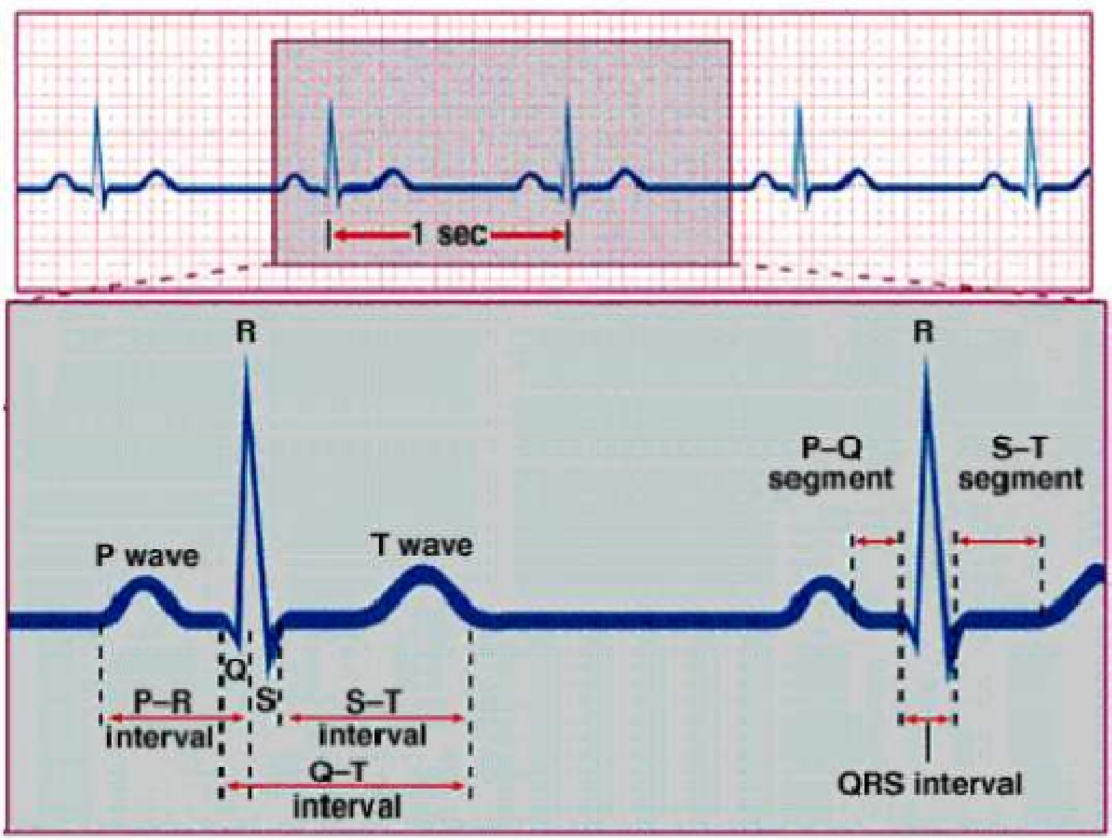
Our objective is to process the EKG signal and extract its key features. The key features will give us a comprehensive picture of the patient's heart health. The features can then be used for things like training a machine learning classifier to predict whether a patient's has a certain heart condition from his EKG signal.

Chapter 2

ECG Signal Overview[1]

2.1 ECG

An ECG is the oldest available tool for measuring electrical activity of the heart. It is a non-invasive procedure that uses leads all over the body to measure electrical current transmitted by the heart to all over the body. A cardiologist diagnoses heart conditions like MI by looking at the characteristics of the ECG signal. There are 3 main things to focus on: the P-wave, the QRS complex, and the T-wave. You can see the different portions in the following diagram:



[1] This content is available online at <http://cnx.org/content/m48314/1.1/>.

Different heart conditions have different deviations from the normal characteristics. For example, one important segment in diagnosing heart conditions is the S-T isoelectric line. A depressed or elevated S-T segment indicates a cardiac ischemia. All the important features can be found if the signal's key points (peaks and points of inflection) and location of the points are known.

Leads are placed in strategic places on the body to measure different heart anomalies. The leads illustrate a comprehensive picture of the heart's activity. Multiple leads are used to detect the propagation of the electrical impulse from different angles relative to the heart. There are positive and negative leads. If the electrical impulse generated by the heart moves toward a positive lead a positive deflection takes place. Similarly, when the impulse moves towards a negative lead, a negative deflection takes place. A total of 12-15 leads are placed on the body. Some are on the chest, and some are on the arms and legs. The result are waveforms that show the physiological condition of the heart.

ECG and Myocardial Infarction

An infarction produces abnormalities in the ECG signal. Through analyzing ECG signals of patients with diagnosed MI and comparing these signals to those of healthy patients, features can be identified characteristic of MI. The abnormalities manifested in the ECG signal are dependent on the location of the infarction. Some key features [5]:

- ST segment elevation or depression
- T wave inversion
- Pathological Q wave
- Increased R wave amplitude

Chapter 3

Method for Correcting Baseline Wander in Raw ECG Signals[1]

Myocardial Infarction (MI) can be diagnosed from a patient's ECG signal by determining if certain features indicative of the condition are present in the signal trace. The infarction can occur in different areas of the heart, giving rise to MI families specified by the location of the infarction.

A patient's raw ECG is inherently noisy due to electric and power line interference, electromagnetic interference, muscle activity, lead placement on the body, and bowel movements. This noise produces a baseline wander in the signal that must be corrected in order to extract features.

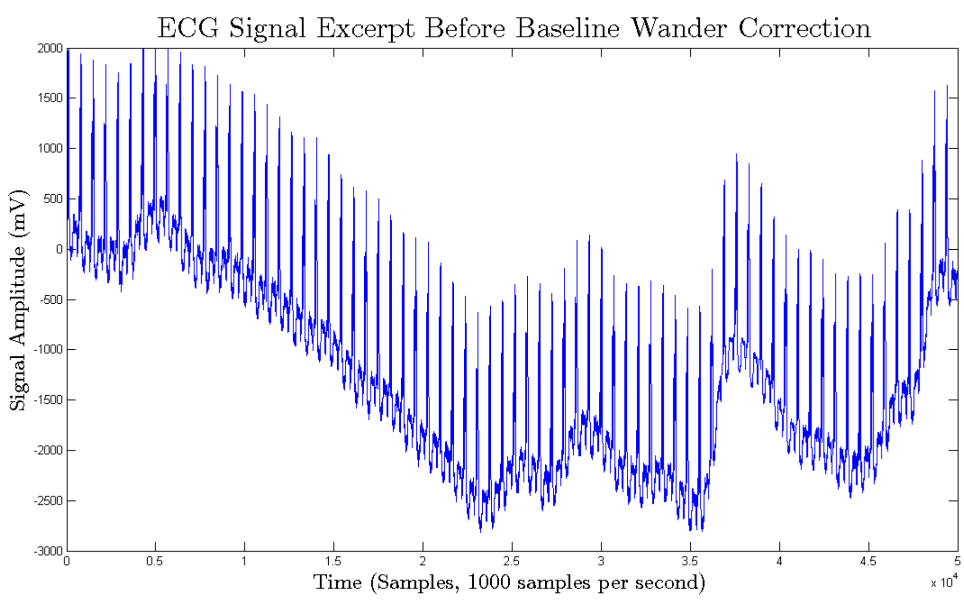


Figure 3.1

[1]This content is available online at <http://cnx.org/content/m48338/1.1/>.

ECG signal analysis relies heavily on identifying a feature and extracting subsequent features from it. Segments in the signal can also be computed from these points of interest and related to one another. Signal drift can introduce error in the extraction of features and comparison between them. Hence, it is necessary to obtain a normalized signal for an accurate analysis.

The process for baseline wander correction is as follows. The raw ECG signal is first filtered with an FIR low pass filter. Second, the filtered signal is passed through a 200 ms median filter to eliminate the QRS complex and then again through a 600 ms median filter to remove the T wave. Then, this signal is subtracted from the low passed filtered signal. The difference between the two signals will constitute the ECG signal corrected of baseline wander.

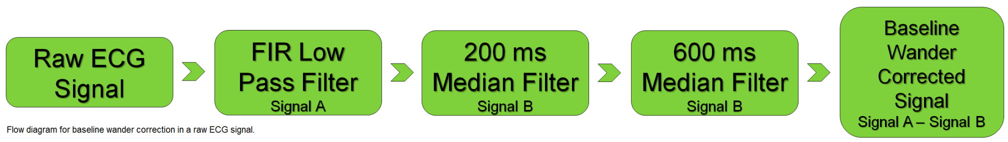


Figure 3.2

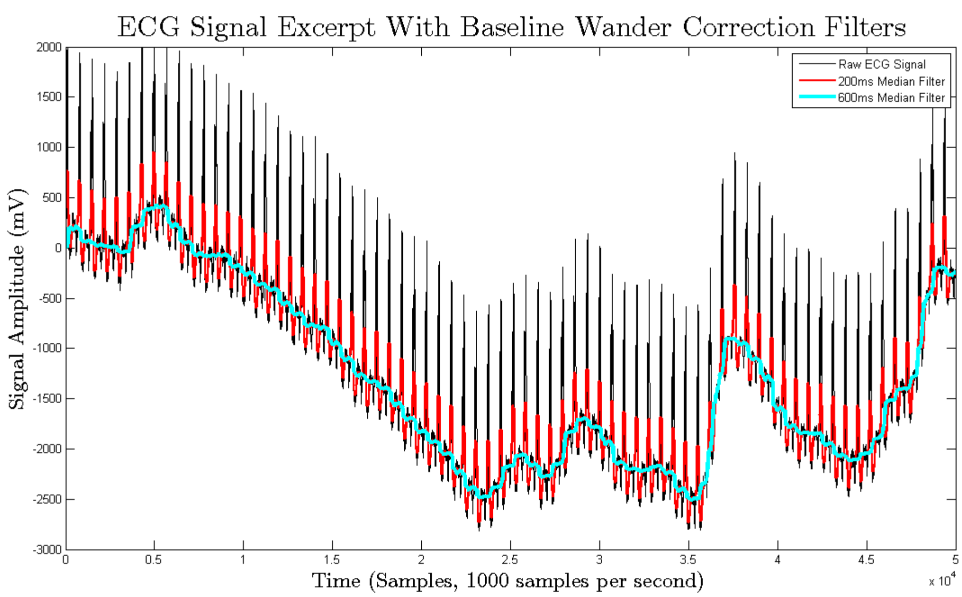


Figure 3.3

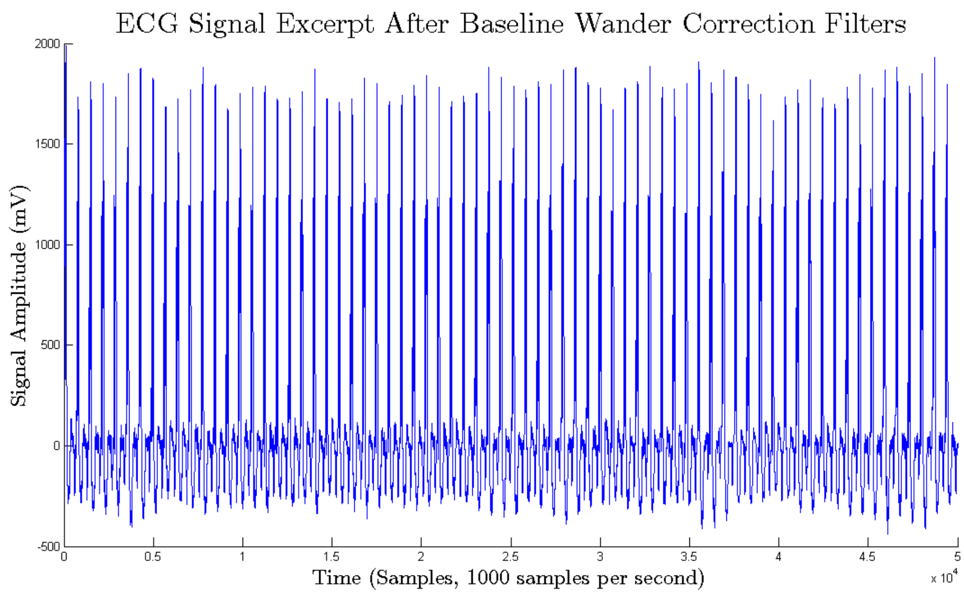

ECG Signal Excerpt After Baseline Wander Correction Filters
Signal Amplitude (mV)
2000
1500
1000
500
0
-500
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
Time (Samples, 1000 samples per second)
x 10^4

Figure 3.4

Chapter 4

Biorthogonal Wavelet Transform - Selecting a Transform for ECG Signal Analysis[1]

Properties of the Biorthogonal Wavelet Transform

Due to the non-stationary nature of the ECG signal, it is imperative to use a transform that preserves the temporal occurrences of the signal's frequencies. The Fourier Transform, although commonly used in signal analysis, fails to do such, so it was necessary to select a transform with properties more suitable for this application. Properties of interest include orthogonality, wavelet function width, mother wavelet shape, and whether the wavelet function is complex or real valued. In ECG parameter extraction a non-orthogonal analysis involves high redundancy at larger scales. The width of the wavelet function, "directly acts on the analysis resolution that is for wavelet the result of balance between the length of analysis of samples window in time frequency axes. The shape of the mother wavelet is of interest as wavelet filtering can be viewed as an adapted filter looking for the highest correlation between the ECG signal to analyze and the considered wavelet. Lastly, "a complex wavelet providing information about both amplitude and phase is better suitable for oscillatory signal behavior whereas real valued wavelet function only returns a single signal modulus that can be used to isolate signal peaks and discontinuities. Further, "it is desirable that the basis functions (wavelets) be symmetric/antisymmetric. A symmetric basis will enable the detection of peak of wave as an extrema. In the case of antisymmetric basis, the peak of the wave is detected as a zero crossing. Second, minimizing the number of sign changes in the wavelet will facilitate the parameter extraction algorithm. In choosing between the various wavelet families, biorthogonal wavelets are a common choice for ECG signal analysis as they satisfy the above properties.

[1] This content is available online at <http://cnx.org/content/m48308/1.1/>.

Chapter 5

Results[1]

After taking the Biorthogonal Wavelet Transform (BWT), features were calculated from the transformed signal. The following figure represents the coefficients of the BWT, along with certain features highlighted.

[1]This content is available online at <http://cnx.org/content/m48368/1.1/>.

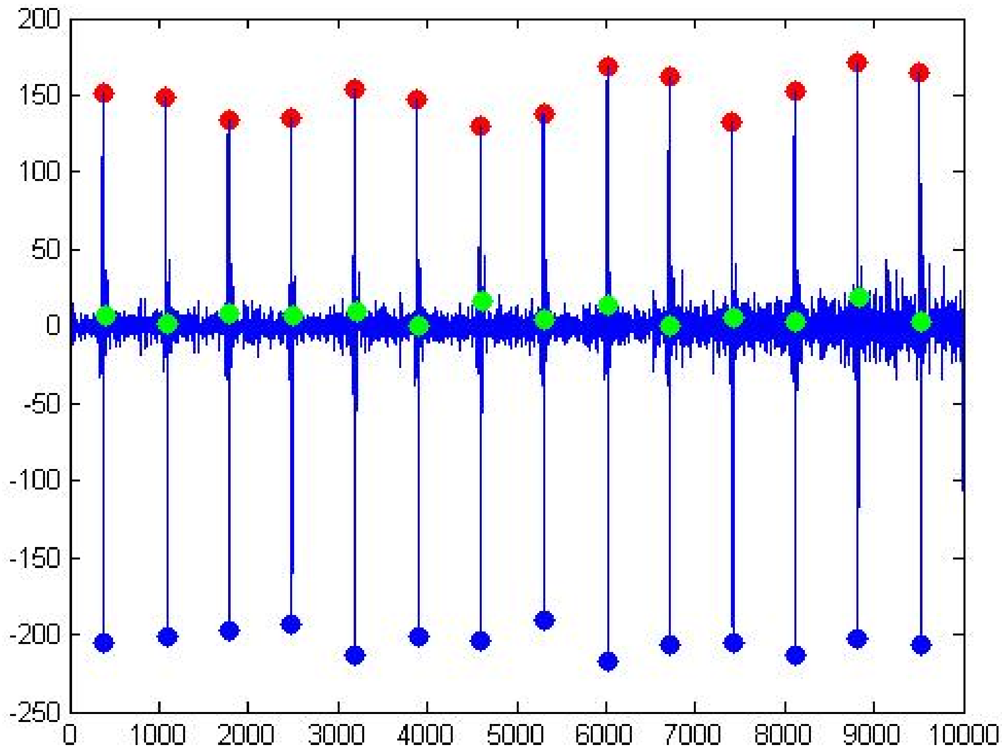


Figure 5.1

Since the BWT conserves the temporal properties of the ECG signal, the features on the raw ECG signal can simply be identified in the transformed signal. The first feature calculated is the R-peak, which is shown in red. This was calculated by iterating through the samples and calculating the local maxima at each QRS segment, after an approximate threshold was used. Once the R-peaks were determined accurately, the heart rate was then calculated. This was done by finding the average time difference between two peaks. Most heart rates were between 70 and 90 bpm. The detection of R-peaks and heart rate lead to the ability of calculating other peaks, particularly the S and J peaks. It is known from literature that the duration of the QRS complex is 60 ms (Thompson 1985). This provides a window for calculation of certain peaks such as the S peak, which would be 30 ms. The J peak is essentially the first inflection point after the S peak. Successful calculations of the S and J peaks are shown in blue and green respectively. These peaks are a basis for the calculation of the main features described earlier, such as the ST-segment and T-wave inversion. Limitations in obtaining accurate calculations of other features were additional noise especially in the QRS complex. The algorithms used to find other features were similar to the one used to calculate S and J peaks, however, this noise would often calculate multiple values, or miscalculate certain values. However, the pre-processing done to the raw ECG were essential to developing the first base peaks as shown. These results are the stepping stone to being able to synthesize a comprehensive amount of features in order to accurately and precisely diagnose Myocardial Infarction.

Chapter 6

Future Work[1]

Future Work

There are a couple next steps that can be taken once the algorithms and filters that extract the features from the input ECG signal have been developed. The first potential step for future work is the development and hardening of the feature extraction filters and algorithms. While much of the ECG signals between patients remains very similar, several environmental factors can affect the signal in ways that make it more difficult for algorithms to detect and identify the appropriate features in question. The second identified potential step for future work is aggregating these extracted features and inputting them into a machine learning classifier. This would create a system which would accept a patient's ECG signal as an input and provide a calculated correlation value comparing it to the signal of healthy patients and patients with Myocardial Infarction. This classification would be able to serve as a tool in the identification and treatment of patients with Myocardial Infarction.

Algorithm Hardening

ECG measurements are taken in a variety of locations with different environmental noise. Additionally, other factors like lead placement are generally similar between measurements but can vary from one case to another. These variances have effects manifested by variations in the ECG signals recorded. One of the major steps in potential future work would be hardening the algorithms for identifying the desired features such that they achieve a high success rate for a wide range of ECG input signals given these environmental variances. This would also significantly help for processing a large batch of ECG signals while ensuring a high reliability of the outputs without fine-tuning for each individual signal.

Machine Learning Classification

With a large set of features identified from a set of ECG input signals, one could then use the data to train a classifier to distinguish between healthy patients and those with Myocardial Infarction. This potential next step of future work would involve aggregating a vector of identified ECG features for a large number of patients and passing them to a classifier along with each patient's diagnosis. The classifier could then be used with the filtering and processing system to serve as a tool to assist with the identification of Myocardial Infarction. Part of the generated data set would be used to train the classifier and the other component would be used to test the effectiveness. It would then be possible to compare the effectiveness of the classifier given different sets of feature inputs and determine which features are the best indicators for accurately identifying Myocardial Infarction in a patient.

[1] This content is available online at <http://cnx.org/content/m48303/1.1/>.

Chapter 7

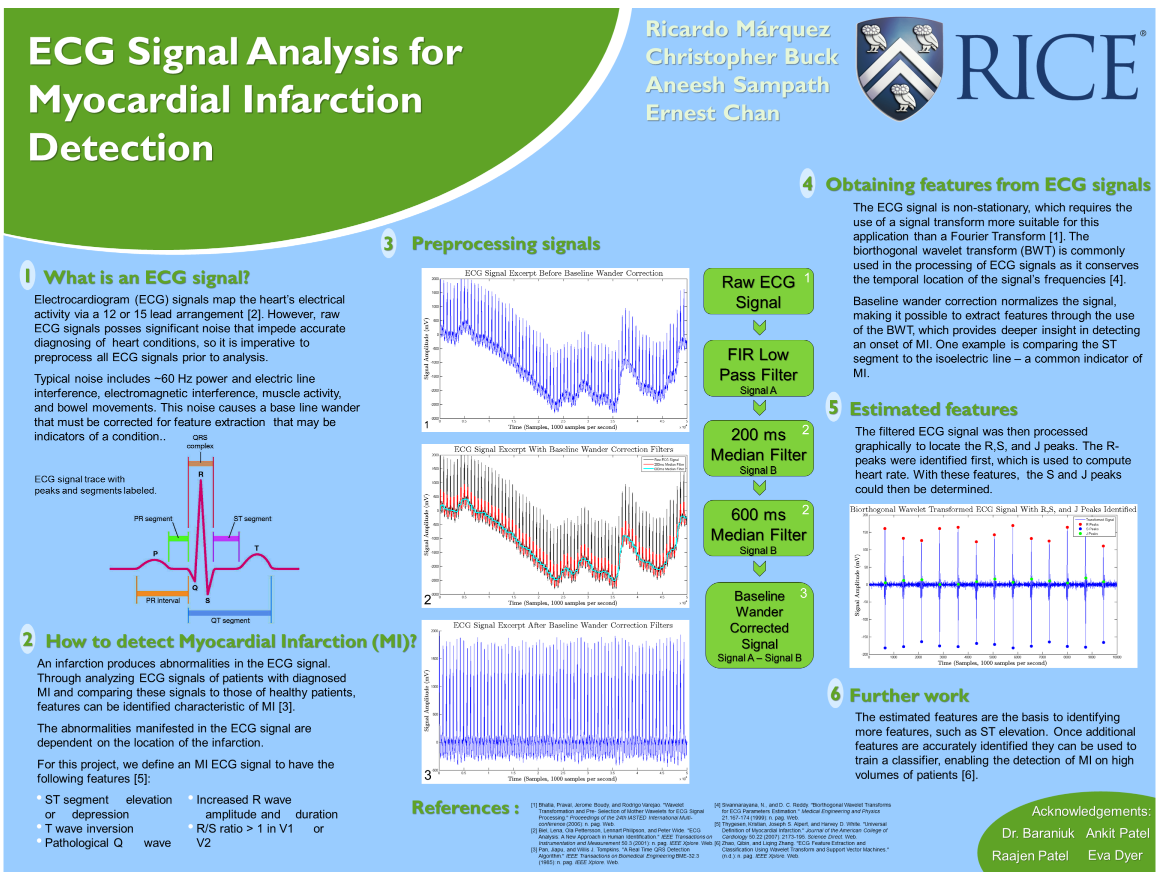
Conclusions[1]

This project demonstrated the use of specific digital signal processing techniques to ultimately develop an accurate procedure to develop base features for detecting Myocardial Infarction. As Myocardial Infarction is a disease that must be diagnosed efficiently, it is imperative to develop a process to accurately and precisely extract features to classify patients. The pre-processing stage of this project focused on fine tuning a raw ECG signal in order to send it through a transform for the accentuation of features. This entailed using FIR low-pass filters as well as consecutive median filters in order to correct for external noise as well as the base wander. The new signal was then sent through a Biorthogonal Wavelet Transform which transformed the signal while maintaining the temporal values of the original signal. The newly refined signal served as a useful reference to analyze the ECG signal and accurately detect the base features, R,S,J peaks, for Myocardial Infarction. From these results, one can more easily detect and synthesize many features in order to train a classifier that can accurately detect Myocardial Infarction.

[1] This content is available online at <http://cnx.org/content/m48404/1.1/>.

Chapter 8

Poster[1]



[1]This content is available online at <http://cnx.org/content/m48367/1.1/>.

Index of Keywords and Terms

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ECG Signal Analysis for Myocardial Infarction Detection
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